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Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization

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ABSTRACT

Artificial intelligence (AI) is increasingly being adopted by organizations, yet implementation is often carried out without careful consideration of the employees who will be working along with it. If employees do not understand or work with AI, it is unlikely to bring value to an organization. The purpose of this paper is to investigate the ways in which employees and AI can collaborate to build different levels of sociotechnical capital. Accordingly, we develop a model of AI integration based on Socio-Technical Systems (STS) theory that combines AI novelty and scope dimensions. We take an organizational socialization approach to build an understanding of the process of integrating AI into the organization. Our framework underscores the importance of AI socialization as a core process in successfully integrating AI systems and employees. We conclude with a future research agenda that highlights the cognitive, relational, and structural implications of integrating AI and employees.

1. Introduction

> *"All too often, AI projects start by trying to implement a particular technical approach, and, not surprisingly, front-line managers and employees don't find it useful, so there's no real adoption and no ROI" -Roman Stanek, CEO of GoodData* (Satell, 2018).

Approximately 80% of large companies have adopted some form of artificial intelligence (AI) into their core business, an increase of 70% in five years (Ghosh, Daugherty, Wilson, & Burden, 2019). AI is relevant for almost every organizational function and is ranked first on the Society for Industrial and Organizational Psychology's top 10 workplace trends list (SIOP, 2020). Scholars agree that AI is likely to become an integral part of the future of work (Huang & Rust, 2018; Wilson, Daugherty, & Davenport, 2019). AI technologies are associated with a plethora of benefits that range from greater efficiency, faster and more accurate results, and reduced error rate at the process level, to more effective and improved strategic outcomes at the organization level (Davenport & Kirby, 2015; Davenport, Guha, Grewal, & Bressgott, 2020; Paschen, Pitt, & Kietzmann, 2020).

AI refers to "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). Ideally, such systems should sense, comprehend, act, and learn (Jarrahi, 2018; Kolbjørnsrud, Amico, & Thomas, 2017), mimicking a person applying intelligence (Haenlein, Kaplan, Tan, & Zhang, 2019). Indeed, today's organizations use AI for highly complex tasks that traditionally require human intelligence, such as selecting applicants for job positions or scheduling logistics (Lawler & Elliot, 1996; von Krogh, 2018), and even for distributing payments to exchange partners in a complex supply chain system through blockchain enabled smart contracts (Murray, Rhymer, & Sirmon, 2020). Similarly, a hospital in Boston successfully utilized machine learning and other AI technologies to create a hyper-local alert system that helped them successfully forecast COVID-19-related clinical demands during the ongoing pandemic crisis (Stevens, Horng, O'Donoghue, Moravick, & Weiss, 2020). Despite the potential for AI to drive organizationally-valued outcomes, however, there is evidence that this often is not the case (Canhoto & Clear, 2020). Many companies invest time, effort, and resources into AI, yet do not experience the anticipated benefits – ultimately deeming AI initiatives a failure (Fountaine, McCarthy, & Saleh, 2019). For instance, a survey of executives by Boston Consulting Group and MIT finds that seven out of ten AI projects generated little impact and that AI implementation plans dropped from 20% in 2019 to 4% in 2020 (The Economist, 2020). Similarly, in a study of senior managers working on 152 AI projects, Deloitte (2017) reports that 47% of respondents find it difficult to integrate AI with existing people, processes, and systems.

Thus, it is clear that in order for AI to be successful, employees must

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embrace, interact with, and integrate their behavior with AI systems (Glikson & Woolley, 2020; Lichtenthaler, 2018). Indeed, scholars indicate that "organizations are entering a landscape characterized by unprecedented collaboration among managers and intelligent machines. There are no maps available yet for navigating through this challenging and unknown terrain" (Kolbjørnsrud et al., 2017, p. 6). Therefore, the interaction between AI and people should be the focal point of AI research in management. This leads to the following broad research question that motivates our current analysis: *How do we bring AI into the organization and successfully integrate such systems and employees to create a sustainable competitive advantage*?

Answering this question is important as organizational scholars indicate that the combination of AI with human ingenuity offers a fertile ground for novel research (Fleming, 2019; Haenlein & Kaplan, 2019; Murray et al., 2020; von Krogh, 2018). The significance of AI and employee integration is clear, especially in practitioner literature and anecdotal evidence (Shrestha, Ben-Menahem, & von Krogh, 2019); yet the investigation of this integration is less developed in the management and organizational academic literature, with few AI related articles published in top management journals that are even "remotely connected" to people and work (Phan, Wright, & Lee, 2017). Moreover, much of the existing research on AI focuses on its technical application (e.g., Barrett, Oborn, Orlikowski, & Yates, 2012). However, AI systems can be active agents in improving strategic decision-making and problem solving (Davenport et al., 2020; Murray et al., 2020), rather than passive receivers of human inputs. Unlike prior technology, AI will have the capability to collaborate, learn from, and adapt to employee interactions. Thus, to successfully bring and integrate AI into the organization, it is important to consider its social aspects.

Accordingly, to answer our research question, we draw from two social processes in the literature – sociotechnical systems (STS) theory and the organizational socialization framework, that are particularly well-suited for exploring future relationships between employees and AI. STS theory highlights the links between technical systems, consisting of technology and processes, and social systems, consisting of people and relationships, and focuses on the joint optimization of an organization's human and technology dimensions within a given context (Manz & Stewart, 1997; Trist, Higgin, Murray, & Pollock, 1963). Socialization refers to the process by which organizational outsiders are transformed into participating and effective insiders (Bauer, Bodner, Erdogan, Truxillo, & Tucker, 2007; Feldman, 1976, 1981; Nifadkar, 2020). We integrate theoretical tenets of STS and socialization with AI literature to frame our research as we aim to enrich the conversation surrounding AI-employee integration by contributing to the management field in two crucial ways.

First, we shape our theoretical contribution by building upon STS theory to develop a unique model of AI-employee integration that indicates when and how these types of collaborations can create sociotechnical capital. In this research, sociotechnical capital refers to the competitive advantage that results from successful collaboration of AI technology and people for adopting organizations. The development of this construct takes a more nuanced and dynamic approach in creating a typology of AI systems to show how employee roles and the nature of its relationship with AI changes, while becoming more complex and layered with the evolution of novelty and scope of AI usage in organizations. This contribution highlights the advantages that can result from the combination of technology and people (Manz & Stewart, 1997; Shrestha et al., 2019; Trist et al., 1963).

Second, we contribute to research on AI by integrating socialization literature that examines how to successfully move an entity from an organizational outsider to an insider (Bauer et al., 2007; Nifadkar, 2020). In doing this, we build upon prior research by highlighting the key features of AI systems and offer a novel framework to delineate how concepts and processes associated with organizational socialization can be applied when bringing AI into the organization to enhance the likelihood of collaboration and integration between AI systems and employees. Accordingly, we argue that using a structured and systematic socialization process to bring AI into the organization is likely to lead to different levels of sociotechnical capital for the adopting organization. Relatedly, we also contribute by identifying employee type and technological readiness of the adopting organization as boundary conditions of the AI socialization process. We begin by reviewing the literature on AI and analyzing key themes that are important for understanding AI-employee integration.

2. Key themes in AI literature

AI has been suggested as the 'Fourth Industrial Revolution' (Syam & Sharma, 2018), which is characterized by a shift in decision-making from humans to machines. Indeed, the fundamental distinguishing feature of AI is its ability to make decisions and to learn and interact accordingly (Haenlein & Kaplan, 2019; Makridakis, 2017). While differentiating AI from prior technological advancements, Syam and Sharma (2018) opine that the close interaction between the physical, digital, and biological worlds sets AI apart from its technological predecessors (p. 136). While the prior technological advancements focused on altering or replacing routine manual tasks, AI involves cognitive, relational, and structural complexities (Kaplan & Haenlein, 2020; Syam & Sharma, 2018). Thus, the changes that occur with AI integration are uniquely different than those of prior industrial revolutions.

Therefore, as we review the literature on AI, we identify how prior research fits into these cognitive, structural, and relational themes, as shown in Table 1. Studies that contribute to the cognitive theme focused more on some of the practical applicability of systems that were built to think or act like humans. Studies with structural themes have contributed to broader discussions of environmental factors involved in the AI adoption process. Last, nascent research in the relational theme briefly summarizes relationships between people and AI, especially along the themes of trust and collaboration.

2.1. Cognitive approach

Mimicking elements of human behavior and higher order thinking provides a goalpost for many that work in development of AI capabilities, like sensemaking work in natural language processing (Weizenbaum, 1966) (NLP) and computer vision (Papert, 1996). The application of novel techniques like machine learning, neural networks, and deep learning is an attractive area for many businesses looking to improve their organizational decision-making ability (Haenlein & Kaplan, 2019; Shrestha et al., 2019; Meinhart, 1966). The combination of man and machine have not eliminated flaws in decision-making such as biases, which appear in models, algorithms (Choudhury, Starr, & Agarwal, 2020), training sets (Cowgill & Tucker, in press), and input incompleteness (Choudhury et al., 2020). Fair, transparent, and explainable AI serve as a step to help mitigate some of these issues (Satell & Sutton, 2019), yet the creation of context-spanning systems that satisfy these criteria are challenging to construct. Nevertheless, the literature shows that newer AI systems are continuously becoming more intelligent and moving from simple task automation activities to having better contextual awareness (Davenport et al., 2020).

2.2. Structural approach

Many organizations recognize the potential of augmenting or replacing employees with intelligent systems, but few have accomplished such aspirations at scale (Barro & Davenport, 2019). Organizations are likely to realize benefits from AI by either building their own innovation ecosystem or joining an existing one that is built by technology partners, suppliers, customers, and other stakeholders (Brock & Von Wangenheim, 2019). An organically generated innovation ecosystem may benefit from a hub and spoke structure supporting AI within the organization, with the 'hub' setting standards, determining training

Table 1
Key themes in AI literature (representative articles).

Theme	Study	Description	Benefits
Cognitive	Satell and Sutton (2019)	Bias may be mitigated with AI that is understandable.	Fair, transparent, and explainable AI may help reduce bias in business processes and operations.
	Shrestha et al. (2019)	Impact on organizational decision-making with the advent AI-based decision-making algorithms.	Increased specificity of the decision search space, better interpretability of the decision making process and outcome, bigger size of the alternative set, more decision-making speed, and enhanced replicability.
	Choudhury et al. (2020)	Bias may be present in AI before they are even applied.	Increased attention to risks of bias in algorithms, models, and inputs may help develop AI for better decision-making.
	Davenport et al. (2020)	Adaptable & context-based AI will provide more powerful resource than specific task-automation AI.	Contextual awareness in AI represents a major leap from task automation and faces many challenges before such systems are successfully deployed.
	Jarrahi (2018)	AI superiority in information processing can augment human thought processes in complex environments.	Design of AI with a goal of augmenting human thought allows symbiotic collaboration in decision-making.
Relational	Glikson and Woolley (2020)	The success of AI critically depends on workers' trust on AI technology.	Higher levels of cognitive and emotional trust will lead to higher levels of AI integration in organizations.
	Huang et al. (2019)	Humans and AI excel at distinct and different tasks.	Optimal collaboration opportunities between AI and humans may involve situations that require a mixture of automated processes (AI) with empathy and emotion (human).
	Mahidhar and Davenport (2018)	Fast follower strategy may not work for companies in the AI adoption context	Collaboration between people and AI create contextualization necessary to capture efficiencies in operating verticals
	Seeber et al. (2020)	Future AI can be viewed as a teammate, not just a tool.	Advanced AI may have capabilities that enable it to work as a teammate with humans, even serve as a leader/task assigner.
	Agrawal et al. (2017)	Advantages may exist for managers who best apply AI.	Managers need new skills to best deploy predictive power of AI, and integrate with human intelligence.
Structural	Barro and Davenport (2019)	Intensity of investment and type of AI output will affect company performance.	Task and job redesign with AI in mind will help deploy people in the right way, while decreasing costs and improving productivity.
	Fountaine et al. (2019)	Full recognition of benefits of AI requires a major retool of the organization.	AI involved in decision-making enable flattened organizational structures and empower employee decision-making at lower levels.
	Brock and Von Wangenheim (2019)	Organizations that participate in or build innovation ecosystems are in a better position to realize benefits of AI.	Organizations that build or are already part of an innovation ecosystem are likely to recognize benefits from AI and other new technologies.
	Lichtenthaler (2018)	Organizations must strategize to find the right interplay between human and AI across a matrix of working together or replacement.	Different situations may call for AI superiority in completing a task, human intelligence superiority, or finding a way to augment human intelligence with AI to solve complex problems.
	Wilson et al. (2017)	AI will create new job types.	AI use will necessitate the creation of entirely new job types and categories.

strategies, ethics, and other managerial topics, while 'spokes' handle responsibilities closer to the use of AI (Fountaine et al., 2019). Building this culture requires a shift to an organization that enables interdisciplinary collaboration, data-driven decision making, and an agile, experimental and adaptable mentality (Brock & Von Wangenheim, 2019; Fountaine et al., 2019). Some studies have considered the structural aspects of a job itself, like the potential for automation (Barro & Davenport, 2019; Lichtenthaler, 2018), the level of empathy required for a job (Huang, Rust, & Maksimovic, 2019), and the novelty of skills required in task design (Davenport et al., 2020).

2.3. Relational approach

The most dominant theme related to the relational approach in the AI literature relates to trust in the AI system (Glikson & Woolley, 2020). Trust in AI may depend on the embodiment of the system (i.e. a robot, virtual agent, etc.) and the level of machine intelligence, mutual concern, a shared sense of vulnerability, and faith in the competence of the system (Glikson & Woolley, 2020; Gray, 2017). Some employees may feel skepticism towards advanced technology like AI due to fears of job replacement, despite a lack of consensus on jobs disappearing or the nature of human-AI collaboration (Brock & Von Wangenheim, 2019; Fleming, 2019; Li, Bonn, & Ye, 2019; Seeber et al., 2020) and increase their competition with other employees due to perceived threats of advanced technology (Schrock, Hughes, Fu, Richards, & Jones, 2016) leading to higher levels of turnover (Gim, Desa, & Ramayah, 2015). Accepting AI as a member of a collaborating team may depend on the design of the system, collaboration, and the institution implementing the AI (Seeber et al., 2020). Some employees may find issues in building trust with a system or teammate that does not actually feel emotions or have the same capability of empathy (Gray, 2017; Huang et al., 2019), leaving managers with a difficult challenge on how to best integrate AI into the organization.

Based on the discussion above, it is evident that much of the current literature of AI in management explicitly highlights applied methods and techniques, indicating, for example, how AI is being or can be applied for a broad range of organizational functions such as assembly lines, customer interactions, human resources, job tasks, and strategic decision-making (e.g., Barrett et al., 2012; Davenport et al., 2020; Jarrahi, 2018; Shrestha et al., 2019; von Krogh, 2018). Moreover, we find that although the relational aspects of AI systems are nascent and emerging within academic research, it is a growing phenomenon of interest in practitioner outlets and organizations. The hybridization of man and machine points to a symbiosis to achieve optimal results, while utilizing the strengths of both people and AI systems (Jarrahi, 2018). Thus, a shift is needed in the study of AI management, from a focus on AI as an application and technique to AI as a collaborator, building understanding of how to effectively integrate it to achieve a competitive advantage for the adopting organization. In the next section, we discuss how different types of AI-employee collaboration may create varying degrees of sociotechnical capital.

3. Building sociotechnical capital through the integration of AI and employees

Our discussion of the pertinent AI literature demonstrates that AI has shifted from the use of simple tools to highly sophisticated systems (Davenport & Kirby, 2015; Glikson & Woolley, 2020) that can have wide ranging effects on the future workplace and employee behavior. Consequently, we believe that it is important for management scholars to better understand the dynamics of different AI systems and employee relationships. STS theory offers one perspective that can help build understanding of how the integration of AI and employees can lead to a competitive advantage for organizations. STS develops a framework to examine how people within a given system interrelate with its technology to affect joint outcomes while being enveloped in a contextual environment (Emery, 1959). Thus, STS theory seeks to "describe and explain the behavior of organizations and their members while providing critical insights into the relationships among people, technology, and outcomes" (Kull, Ellis, & Narasimhan, 2013, p. 66).

As such, STS theory helps build the case for sociotechnical capital, or what we define as the combination of AI technology and people in organizations that leads to a source of competitive advantage for an organization. We extend work by Resnick (2001), who indicates that sociotechnical capital refers to "productive combinations of social relations and information and communication technology" (p. 3). In his conceptualization, Resnick (2001) describes sociotechnical capital as a subset of social capital focused on the technological medium of interactions. He argues that individuals can foster sociotechnical relations through email, social media, and other technological applications, particularly in the community and in building civic virtual engagement. We propose, however, that the sociotechnical capital construct can be expanded to the work domain and modified to reflect the ability of the organization to jointly optimize the use of AI and people. Sociotechnical capital is likely to result from the successful integration of AI technology and employees where both the entities act as a tightly coupled system exhibiting increased responsiveness (Morgan-Thomas, Dessart, & Veloutsou, 2020; Orton & Weick, 1990). Like other forms of capital, sociotechnical capital can be accumulated over time with intentional investment. As such, it can be considered an intangible resource that is valuable, rare, difficult to imitate, and organization-specific that may be utilized to build a sustainable competitive advantage (Barney, 2001). Prior research suggests that capital is valuable only to the extent to which "an organization is able to integrate and utilize" the resource (Raffiee & Byun, 2020, p. 37).

As intelligent systems continue to evolve and become more pervasively adopted by organizations for a broader range of tasks, they will change employee roles and the nature of the AI-employee relationship also is likely to become more complex. Thus, the *novelty* of such systems and the *scope* of their applications in the adopting organization are two salient dimensions in this regard. As shown in Table 2, we develop a "Model of AI Integration" in the workplace that combines the level of AI novelty (low/moderate/high) and the scope of AI (content changing/incremental AI versus context changing/radical AI) dimensions. "Content changing" refers to the changes occurring in a narrower task domain, mainly based on the component knowledge of the associated system (Davenport et al., 2020; Dewar & Dutton, 1986; Henderson & Clark, 1990). "Context changing" refers to the changes that may occur in broader task domains (and sometimes across the value chain creating new ecosystems) (Davenport et al., 2020) based on the architectural knowledge of the system (Mukherjee, Lahiri, Ash, & Gaur, 2019). The typology highlights the types of employee-AI relationships and human roles in working with different types of AI. The resultant quadrants entail six types of AI and associated human-AI relationships and human roles. Each of these combinations produces various levels of sociotechnical capital in organizations.

Quadrant Ia focuses on '*automation*,' or AI systems that are focused on narrow task domains such as assembly line robots or automated virtual assistants. This quadrant represents routine automation of work and is typically associated with lower human skill levels that can be substituted with more efficient AI systems. The negative perceptions and job security-related apprehensions associated with AI is highest in this quadrant as these AI systems tend to replace redundant human employees. The role of employees is that of a 'controller' where the employee provides necessary inputs to the AI system to obtain a predetermined level of output. The work is done faster, and the results are often more accurate. We consider the scope of the AI systems in this quadrant as narrow because such systems are focused on a particular functional area and cannot perform other tasks. Yet, the automated systems and the robots used by today's workforce have come a long way and require meaningful human-machine interaction. A case in point are "cobots" — robots with contextual awareness (Wilson & Daugherty, 2018). These machines work alongside human employees; while cobots are engaged in repetitive functions involving strength, endurance, and precision, employees perform tasks that warrant human judgment (Wilson & Daugherty, 2018). This quadrant will likely result in low levels of sociotechnical capital, as not much integration can occur between AI systems and employees. While some degree of coordination is required between the employees and automated AI systems, the degree of interdependence remains low, leading to low levels of sociotechnical capital.

In quadrant Ib, AI systems can be used across several organizational functions and are considered to have an '*amplified*' effect that can produce moderate sociotechnical capital, as collaboration between these types of AI systems and employees may be more productive than either on their own. For instance, AI systems such as predictive analytics can learn from data and make accurate predictions and transaction level decisions that are detailed in nature about a wide array of factors (Desouza, Dawson, & Chenok, 2020). However, the data input feeding process and interpretation of the outputs are still conducted largely by human employees, with their role being more like that of a 'conductor,' ensuring that interpretation is meaningfully integrated with the strategic decision-making process of the focal organization. We consider the level of sociotechnical capital produced in this process as 'moderate,' as the AI systems and employees are still loosely coupled. While results produced by such AI systems are integrated in strategic decision-making, both entities still retain their separateness and identity (Orton & Weick, 1990).

Quadrant IIa is comprised of the AI systems that '*augment*' human abilities. Such systems are moderately novel and are focused on specific

Table 2
AI integration model.

Level of AI Novelty	Scope of AI: Content Changing AI	Scope of AI: Context Changing AI
High	**Autonomous** (Self driven vehicles) **Employee-AI Relationship**: Independence **Human Role**: Keep in Check IIIa	**Authentic** (Superintelligence) **Employee-AI Relationship**: Singularity **Human Role**: Comprehend IIIb
Medium	**Augmentation** (Robots in Surgery) **Employee-AI Relationship**: Complementary **Human role**: Collaborator IIa	**Alteration** (Deep Learning) **Employee-AI Relationship**: Symbiotic **Human Role**: Co-creator IIb
Low	**Automation** (Assembly line robots, DSS, automated online assistants) **Employee-AI Relationship**: Substitution **Human Role**: Controller Ia	**Amplification** (Predictive AI) **Employee-AI Relationship**: Supplementary **Human Role**: Conductor Ib

content areas. For example, surgical robots used in complicated surgeries by physicians who are striving for better patient outcomes often lead to shorter hospital stays and faster recovery while simultaneously increasing surgeons' productivity rate (Musib et al., 2017). The employee-AI relationship is considered complementary and the human role is that of a collaborator as the usage of the systems requires a close hand-in-hand interaction between the two parties. We anticipate that this quadrant would result in high levels of sociotechnical capital as the two entities (i.e., humans and AI systems) act more like a tightly coupled system while still retaining some degree of independence and distinctiveness.

Quadrant IIb involves '*alteration*,' or AI systems that are more novel and 'co-create' unique outputs with human employees, leading to the highest levels of sociotechnical capital. This quadrant contains AI technologies that can fundamentally change the way work is currently performed and will impact the future workforce spanning multiple platforms and industries, which will entail very profound and 'symbiotic involvement' between AI systems and humans. As the interdependence between the two entities is almost inseparable, the system exhibits high responsiveness. Organizations in this quadrant would develop their processes and toolsets around human-AI centered systems, which would acknowledge the value of this nexus of interactions. This contrasts with developing exclusively human-centered systems or organization-centered systems (Kling et al., 1998). The interaction between AI and humans would serve as the center and focal point of the organization as change occurs balancing the requirements of both parties simultaneously.

Consider the following case, which highlights the usage of deep learning neural networks to invent new drug compounds. A new AI tool, developed by Marwin Segler and his colleagues at the University of Münster in Germany, "uses deep-learning neural networks to imbibe essentially all known single-step organic-chemistry reactions — about 12.4 million of them. This enables it to predict the chemical reactions that can be used in any single step. The tool repeatedly applies these neural networks in planning a multi-step synthesis, deconstructing the desired molecule until it ends up with the available starting reagents" (Else, 2018). This AI system learns exclusively from data and does not require human input. The chemists then use the resultant output to develop the desired drug, resulting in greater performance benefits for the organization. This example signifies a deep level of 'symbiotic involvement' between the machines and human, where the strength of the dyadic relationship hinges not only on mutual knowledge and cognition, but also on affective factors such as trust and confidence in the outputs derived by the former. Consequently, the sociotechnical capital produced in this quadrant is most difficult to imitate by rival organizations as they are embedded in the organizational structure in complex and causally ambiguous ways.

The AI systems in Quadrant IIIa continue to evolve to '*autonomous*' machines that are highly sophisticated in narrow content areas. The human role in this case is to keep the systems in check so that ethical and legal boundaries are not crossed. For example, Sophia, a robot that was given citizenship by Saudi Arabia, can use facial recognition, process visual data without ongoing human interference, and is capable of displaying fifty facial expressions. Another example is the strides made by scientists creating AI systems that are capable of detecting human emotion and acting accordingly (Kaplan & Haenlein, 2019). For instance, AutoEmotive, Affectiva's Automotive AI, is capable of detecting human emotions such as anger or attention lapse. Scholars believe that such systems can be effectively used to prevent accidents or road rage incidents (Kleber, 2018). Algorithmic management, or management systems that have the ability to learn about and make decisions about employees, may also be void of moral authenticity (Jago, 2019) and lack true empathy applied by human managers (Duggan, Sherman, Carbery, & McDonnell, 2020). At this point, these AI systems are largely autonomous, albeit focused in narrow content domains. The human role is that of a 'checker' or a 'moral guardian' and the AI-employee relationship is independent of one another. Employees may reside in an AI center of excellence to play the role of ethicist (Davenport & Dasgupta, 2019). Because this quadrant involves some interaction between AI and employees, moderate levels of sociotechnical capital may result.

Finally, quadrant IIIb is considered '*authentic* AI' or a "black box' where the AI systems are futuristic and superintelligent. This is what AI is striving for—machines or systems that act, think, and learn like humans or are capable of completely surpassing them (Barrat, 2013). The possibilities are limitless and the human role in such instances will be to 'comprehend' and coexist with such systems. At this stage, the machines will neither depend on humans for input nor will need supervision. Some researchers predict that such AI (also known as "artificial general intelligence") will possess self-awareness, empathy, and consciousness of their own, thereby creating a different future for this world (Müller & Bostrom, 2016). The AI-employee relationship is largely speculative in this quadrant, but likely would not generate much, if any, sociotechnical capital due to the 'singularity' of AI in these systems. In an informative interview with an expert who works with organizations to implement AI, we learned that such systems may produce bias and risk mitigation challenges because of low comprehension of the underlying model.

While we focused our analysis on six ideal configurations, in practice, there may exist hybrid forms of AI systems and AI-employee relationships that cross the boundaries of individual quadrants. Thus, the resulting quadrants should be treated as ideal scenarios. As AI systems continue to become more complex, far reaching, and novel, the ideal types described in our typology may move from one quadrant to another. Moreover, some narrow, content changing AI systems may have broader context changing applications in the adopting organizations as such systems developing more 'contextual awareness' and having more self-learning capabilities (Davenport et al., 2020). Such context changing applications of AI systems in new domains will also depend on employees who use such systems and find new ways to apply them within the organization.

4. Towards a framework for AI socialization

To develop sociotechnical capital, organizations need a structured approach for bringing AI into the organization. Organizational socialization formally refers to "the process by which newcomers make the transition from being organizational outsiders to being insiders" (Bauer et al., 2007; p. 707), and is a widely accepted systematic way of bringing people into an organization and integrating them with others. Accordingly, we seek to make progress in navigating AI and employee collaboration by presenting a comprehensive framework for AI socialization (see Fig. 1), which integrates AI literature with research in organizational socialization and employee onboarding (Bauer et al., 2007; Kammeryer-Mueller & Wanberg, 2003; Saks & Ashforth, 1997; Van Maanen & Schein, 1979). The socialization process helps a work environment become more stable and understandable (Saks & Ashforth, 1997). This is important when dealing with AI systems which are fraught with uncertainty (Frey & Osborne, 2017).

The socialization process helps whenever "there are changes – small or large – to a role, tasks, or job context" (Klein & Polin, 2012). AI is still considered a newcomer in many companies but is rapidly becoming a pervasive organizational phenomenon (Paschen et al., 2020; von Krogh, 2018). AI systems with a built-in learning component must undergo some level of socialization to alter processes and procedures for its unique operating environment. This may necessitate such a system altering some of its activities using learning techniques to provide the best level of service and collaboration for stakeholders. For instance, a collaborative AI embodied in a robot meant to help nurses and doctors may need to develop slight variations of solutions, and ways to communicate those solutions, for each stakeholder or hospital it operates in (Beans, 2018).

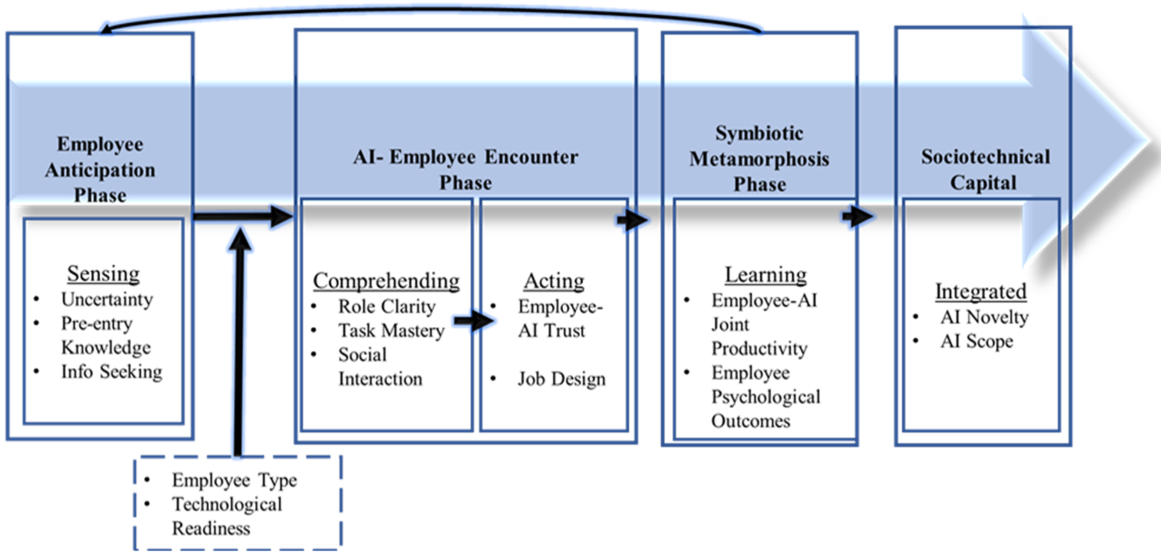

Fig. 1. Systematic framework for AI socialization.

Thus, successful socialization may help alleviate negative expectations and usher in a better structure to amplify the abilities of both humans and AI-based systems (Groom & Nass, 2007). Models of organizational socialization include anticipatory predictors, encounter processes, and metamorphosis outcomes (Bauer et al., 2007; Fang, Duffy, & Shaw, 2011; Feldman, 1976; Kammeryer-Mueller & Wanberg, 2003; Saks & Ashforth, 1997; Van Maanen & Schein, 1979). We build upon these baselines and combine them with the four key features of AI systems that distinguish them from other technological advances – sensing, comprehension, acting, and learning (Kolbjørnsrud et al., 2017) – to provide a systematic framework of AI socialization.

Sensing refers to the ability and process to capture information (Ramos, Augusto, & Shapiro, 2008) such as machines in an autonomous environment having the ability to use perception to discover their operational problem space (e.g., Apple's Siri receiving elements from the environment). In our framework, we indicate anticipatory predictors of AI integration that help employees make 'sense' of AI applications including managing uncertainty, pre-entry knowledge, and information seeking. *Comprehension* refers to the ability to analyze and understand information collected (Kolbjørnsrud et al., 2017), such as a problem-solving process using induction and deduction to search for the optimal solution or action to take next. *Acting* refers to the ability of the system to "make informed decisions or recommend action" (Kolbjørnsrud et al., 2017, p. 8), such as an Amazon Robot in a warehouse sensing a box on the ground, comprehending that it is not supposed to be in its path, and taking action to move the box to where it belongs. In our framework, these processes are expected to be important during encounter socialization as 'comprehension' and 'action' strategies highlight tactics such as role clarity, task mastery, team development, and social interaction. Last, *learning* refers to the ability of a machine to gain skills from the experience of previous processes and actions (Kolbjørnsrud et al., 2017). One example of this is a chatbot named LiLi that is able to formulate and execute strategies that help it acquire and deploy new knowledge in conversations with humans in a continuous manner (Mazumder, Ma, & Liu, 2018). In our framework, we discuss employee and organizational learning as indicators of metamorphosis, or full assimilation of AI into the organization where employees gain skills in collaborating with AI systems. If this process is successful, we propose that the final result will be varying levels of sociotechnical capital that will help provide a competitive advantage for an organization.

4.1. *Anticipatory predictors: Making sense of AI systems*

Before AI is brought into the organization, managers need to help employees make sense of AI systems. They can do this by assessing uncertainty and pre-entry knowledge that employees have of AI systems and creating a formal AI onboarding plan (Bauer, 2010). AI, especially in combination with robotics and emotion-sensing capabilities, may lead employees to respond much differently than computers, smartphones, and other general technologies (MacDorman & Ishiguro, 2006). Moreover, recent surveys reveal substantial apprehension regarding the possible negative effect of AI on employment and other employee-related factors (Fleming, 2019). However, in a recent report on the *Changing Nature of Work*, the World Bank indicates that "while the idea of robots replacing workers is striking a nerve, the threat to jobs from technology is exaggerated – and history has repeatedly taught this lesson" (The World Bank, 2019). Some researchers argue that robots are not likely to steal jobs, but jobs are likely to change and new jobs are likely to be created (Fleming, 2019).

Many employees experience uncertainty regarding what AI will do to them or their jobs and could be better educated about the types of opportunities AI can create. For instance, a recent Accenture study indicates that 36% of managers fear that AI will threaten their jobs, but 84% said they expect AI to make their job more effective and interesting. The study warns that "if leaders fail to account for resistance and apprehension… adoption strategies [of AI] could die" (Kolbjørnsrud et al., 2017, p.39). Moreover, employees who fear they will be replaced by Smart Technology, AI, robotics, and algorithms (STARA) experience higher turnover, cynicism, depression, and have lower organizational commitment and career satisfaction (Brougham & Haar, 2018). Addressing these issues during anticipatory socialization can help the implementation of AI systems to be more successful. In this stage, managers should focus on the 'inform' aspect of Klein and Heuser (2008) onboarding framework. The inform stage of onboarding would address ambiguity and negative anticipation that may be expected when considering implementing AI systems. Because AI systems can be heavily integrated with employees and change the nature of work, this is an essential step in the socialization process.

In particular, Klein and Heuser (2008) suggest that informing employees should include communicating efforts, providing resources, and offering training programs. It is necessary to use agents (managers, HR, etc.) to communicate and help employees make sense of AI systems before they are implemented. Non-technical team members should understand how AI systems work, and what kinds of problems AI systems are good at solving as well as those that AI should not be used for, such as ethical dilemmas or people problems (Martinho-Truswell, 2018a, b). A written AI onboarding plan should include a roadmap with a timeline, goals, and support available during the implementation of AI systems and allow for greater consistency in application across the organization and over time. Stakeholder meetings should consist of managers and HR meeting with employees during the AI implementation process to allow two-way conversation, questions, and issues being resolved before evolving into larger problems.

In addition, providing resources would be a valuable component of the inform stage (Klein & Heuser, 2008; Klein & Polin, 2012). These resources could include coaches, websites, a hotline, or guides that help employees navigate the transition during the AI onboarding process (Klein & Polin, 2012). Employees would then have the opportunity to access resources at their convenience to find information relevant to AI. Providing formal training opportunities related to the AI systems would also be beneficial prior to implementation. In Finland, for instance, private companies and the government provide national support to train non-technical experts in the basics of AI with the goal of becoming a world leader in practical applications of AI (Delcker, 2019). Training during anticipatory socialization may include a shift in focusing on skills that rely on prediction to skills that are more judgement-oriented. Such reskilling may help subside fears of AI systems (Aleksander, 2017). For example, AI can diagnose medical conditions, but employee judgment will be needed to understand the patient and situation and determine what care and treatment may be best.

4.2. Encounter processes: Comprehending and acting

During encounter socialization, managers must aid in employee comprehension and actions in using AI. Comprehension refers to implementation factors, such as clarifying roles, determining task mastery, and figuring out social interactions (Bauer et al., 2007). In the case of AI implementation, employees need to understand the purpose of AI, specifically what its role will be on the team, and how it changes employee roles. *Role clarity* involves building understanding of expectations of a role (Bauer et al., 2007). Clear expectations of the jobs of AI systems and how they are different from or relate to tasks completed by employees will be essential. *Task mastery* is similar to self-efficacy and reflects gaining confidence in one's ability to successfully fulfill job responsibilities (Kammeryer-Mueller & Wanberg, 2003). *Social interactions* are an important part of adaptation and can serve as a sign of adjustment (Bauer & Green, 1998). As AI systems continue to increase in their sophistication and complexity, employees may interact and collaborate professionally and socially with them. Many companies are now using collaborative robots that work with employees to accomplish tasks. At Amazon warehouses, employees paint AI robots to give them personalities (e.g., an AI robot with fiery flames is known as "Devil Drive") (Gonzalez, 2017). Moreover, research has demonstrated that social rules such as politeness are used even when interacting with machines (Nass, Moon, & Carney, 1999). These factors build identities around AI systems and allows collaborative interactions between AI systems such as robots and employees. Interaction comprehension is an important step for the AI system to build an understanding of how it will interact with human users and observers (Mahidhar & Davenport, 2018).

Action refers to change factors relating to trust development and job design. Moreland, Levine, and McMinn (2001) indicate the importance of socialization in the work group, focusing on processes like role transitions and trust development. *Trust development* depends upon two interdependent factors in the socialization process. First, how well the newcomer (AI system) fits into the group and second, the reciprocal impact the newcomer has on the group (Anderson & Thomas, 1996). Human-machine trust depends on performance, process, and purpose of AI systems (Glikson & Woolley, 2020). Dispositions, situations, and past experiences can influence how likely employees are to trust and integrate AI systems into the work group (Hoff & Bashir, 2015). Managers and HR should ensure that elements such as the purpose of the AI system and the process by which it works are well understood to enhance trust.

Job design focuses on the nature of the work itself and how it changes when a newcomer enters the group (Morgeson & Humphrey, 2006). The level of interdependence, autonomy, and feedback between AI and employees will be important factors to consider in the AI socialization process. For instance, AI systems may be part of upper-level management teams in the future, assisting in decisions and helping reduce some of the biases in implementing the organizational vision (Pearce, Conger, & Locke, 2008). Senior-level executives may be left to ask the right questions and seek out difficult-to-acquire information, interpret output and machine decisions, deal with "exceptions" that deviate from the norm, cope with ambiguity, and employ soft skills (Dewhurst & Willmott, 2014). Other roles may include "explainers" who interpret output, "trainers" that work to improve AI systems, and "sustainers" who monitor AI performance (Wilson, Daugherty, & Morini-Bianzino, 2017). Moreover, AI systems will help employees amplify cognitive strengths, interact more effectively, provide autonomy for higher-level tasks, and embody physical characteristics (Wilson & Daugherty, 2018). Even if a complex system exists with decision-making and action-taking power, factors like changing social constructs, complex social interactions, the ability to balance new information, values, emotions, vision, and the overall change are difficult for AI to handle on its own (Parry, Cohen, & Bhattacharya, 2016).

4.3. Boundary conditions: People and context

Theoretical frameworks such as STS and socialization indicate the 'what' and 'how' conceptualization of AI integration in examining a structured process to bring AI into the organization and develop sociotechnical capital. Yet boundary conditions in this process are important to consider as they refer to the 'who' and 'where' aspects of theoretical development (Busse, Kach, & Wagner, 2017). We examine two boundary conditions in our AI socialization model that help us explore the 'who' (people) and 'where' (context) contingencies in the relationship between anticipatory and encounter socialization. In particular, we investigate the role of employee type and technological readiness context as factors that may change the relationship between anticipatory sensing socialization and encounter experiences during the AI socialization process.

4.3.1. Employee type

First, we examine the role of employee type, arguing that service facing frontline employees (FLEs) may have different AI expectations and experiences than manufacturing or higher-level employees who interact mainly with others inside the organization. Socialization with AI assumes a modern service encounter, termed "service encounter 2.0" by Larivière and colleagues (2017), which goes beyond the relationship between a customer and a service provider to include interrelated technologies, people, and both physical and digital environments. In many cases, these complex systems comprise and therefore reap benefits from the expertise of many parties – human and non-human alike – yet managers and employees often face a great challenge in gaining acceptance and usage of such innovative services (Biehl, Prater, & McIntyre, 2004). These services are often perceived as inherently risky due to the lack of human connection; thus, a preference for personal contact with a service employee in the service interaction seems to prevail. Relational elements such as trustworthiness and collaboration with a service employee are important to the perceived effectiveness of the technology from the consumer perspective (Wünderlich, Wangenheim, & Bitner, 2013).

For example, in an informational interview with a research and design employee who created AI applications in the entertainment industry, due to the humanlike nature of AI systems, it is important that employees perceive that an appropriate social hierarchy is in place; that is to say, that their social status is higher than that of the AI system (Tiedens, Ellsworth, & Mesquita, 2000). He conceptualized this as designing AI features for FLEs and consumers to interact with people similar as they would to a pet, which helps set the expectations and context for integration and use. These factors enhance the ease of use and likelihood that service employees will comprehend and engage with the AI and make it more likely that they maintain it (i.e., fix issues that come up, take care of the AI robotic like they would a pet).

As customer acceptance of the modern service encounter grows, employees are not only tasked with managing consumer demands for and interactions with smart technology as a part of the service encounter, but also co-creating value with the technology on behalf of the organization. Smart technology can empower frontline interactions by learning or enabling learning across such interactions (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017). Given that the locus of control is increasingly shifting to the end user (Matzner et al., 2018), it is imperative that smart services delivered through intelligent products not only increase efficiency for customers but are viewed by companies and their FLEs as mechanisms for increasing productivity (Wünderlich et al., 2013). FLEs directly interact with customers and add value to an organization in ways that can contribute to customer loyalty (Briggs, Deretti, & Kato, 2020). Thus, we suggest employee type as a boundary condition in the relationship between AI sensing and comprehending socialization that highlights the importance of FLEs in the AI integration process. Specifically, FLEs in service sectors may have greater difficulty adapting to AI systems, thus weakening the sensing-comprehending relationship and needing additional support from organizations.

4.3.2. Technological readiness

Second, we examine the 'where' aspect of boundary conditions by analyzing the technological readiness context in which the AI system is embedded. Technological readiness is a firm-level capability regarding the use of technological assets (Parasuraman, 2000). It incorporates the context and readiness to use the technology – similar to a climate or willingness to learn (Ray, Muhanna, & Barney, 2005). Employees that belong to organizations with a higher degree of technological readiness may be in a better position to rapidly assess, prepare, and integrate new AI systems as part of their team. Technology-oriented organizations are more capable and willing to leverage new advances in technology as part of the development of new products or services (Gatignon & Xuereb, 1997). In an informational interview with a consulting organization implementing AI for different organizations in the transportation industry, we learned that employees were more likely to comprehend and accept AI systems when they had technological readiness in context. Our interviewee indicated that the most successful companies in implementing AI had a "desire to understand the results of the system and the data behind it" and a "desire to drill down deeper into the results." Technological readiness may moderate the relationship between the sensing and comprehending phases of the socialization model such that those employees who belong to organizations with higher levels of technology-readiness capabilities will be more motivated to act upon information provided by or with an AI system and experience a smoother encounter process to the introduction of AI systems.

4.4. Metamorphosis outcomes: Employee learning

Metamorphosis socialization focuses on employee learning outcomes (Anderson & Thomas, 1996; Saks & Ashforth, 1997). Once AI has been successfully assimilated into an organization, employees are more likely to experience better psychological outcomes and higher performance. Research suggests that effective socialization can lead to greater productivity as well as higher commitment and lower turnover from employees (Kammeryer-Mueller & Wanberg, 2003; Wanberg & Kammeyer-Mueller, 2000). Relatedly, a greater understanding of AI can influence emotional states and career satisfaction (Brougham & Haar, 2018).

In particular, AI is expected to improve productivity by automating routine tasks and allowing employees to focus on work that adds more value to the organization. Employees and AI have many complementary skills, meaning that AI systems combined with humans perform better than either could do alone (Jarrahi, 2018). Research has demonstrated that when humans and AI work together, optimal and improved outcomes can result. Reading radiology images is one such example. While AI had a 7.5% error rate when operating on its own and employees had a 3.5% error rate operating on their own, combining the work of people and AI machines dropped the error rate to 0.5% (Wang, Khosla, Gargeya, Irshad, & Beck, 2016). In addition, research of 1075 companies in 12 industries finds that the more structured the collaboration between humans and AI, the better the AI initiatives performed in terms of flexibility, speed, cost, revenues, and other operational measures (Wilson & Daugherty, 2018).

Collaboration between humans and AI has also shown to increase the IQ of business teams (Wilcox & Rosenberg, 2019). Shirado and Christakis (2017) find that AI technology helped human players enhance their performance in an online game, shortening problem solving time by 55.6%. As such, we expect that greater productivity and better psychological outcomes will occur when a structured approach is used to integrate AI into an organization. These outcomes would provide a feedback loop to the anticipation phase to inform companies how to bring AI into the organization. If the AI socialization process is implemented successfully, we believe it will result in sociotechnical capital that can provide a sustainable competitive advantage through AI-employee.

5. Implications for AI and organizational scholarship: Future research agenda

Our analysis and the socialization model of AI is aimed at stimulating discussion about how to successfully integrate AI into the organization. Additionally, the ideas we present pave the path for future scholars to meaningfully contribute to this discussion. It is widely accepted that cognition and behavior are central constructs driving organizational goals and outcomes (Phan & Wright, 2018). These two constructs manifest themselves through strategic decision-making, while influencing relational outcomes, and shaping organizational design and structure at different levels. Thus, while AI-centric research in the management literature can take many shapes and forms, consistent with the theme of our paper, we highlight the cognitive, relational, and structural implications of integrating AI and employees (see Table 3 for an overview).

First, our framework for AI socialization creates opportunities for research on cognition at the individual (decision-making) and organizational (learning) level, as well as for knowledge management. Second, our framework provides relational questions about integrating AI onto a team, drawing attention to issues related to teamwork, identification, and coordination. Third, we build upon our framework to provide recommendations for structural human resource and organizational issues such as training and job design.

Behavioral theory of the organization (Cyert & March 1963) and its related theoretical frameworks of organizational learning (March, 1991) and knowledge management literatures (Grant, 1996) should form the foundation of cognitive scholarship in AI. A key area of cognitive scholarship on AI should is decision-making (Kaplan & Haenlein, 2020; Shrestha et al., 2019). Although some AI systems can make decisions on their own, there are questions as to how decision makers trust the output that they are receiving from an AI program and understanding how the system arrived at that outcome (Gunning, 2017). What happens when a system suggests something that a lifelong employee sees as foolish? Will the system or the employee be given favor?

Table 3
Future research agenda on organizational implications of AI-employee integration.

Cognitive Issues	Relational Issues	Structural Issues
Strategic Decision Making • How do decision makers trust the output received from AI systems? • What controls in decision making processes are needed when AI system encounters an abnormality that requires human interaction?	**Teamwork** • What is the ideal team size and configuration of AI systems/robots and employee team members? • What are the team dynamics of working side-by-side with AI systems/robots?	**Job Design** • What is the level of AI and employee interdependence? • How will employee tasks change with AI systems?
Organizational Learning • How does transformational learning occur with AI systems? • How does deep learning drive the organizational learning architecture in AI systems?	**Trust and Identification** • How can team identification be fostered between AI and employees working in a group? • How can employees build trust with an AI system/robot?	**Training and Development** • How can we reskill workers to work successfully with AI systems? What type of technological and relational training is needed for nontechnical employees working with AI systems?
Knowledge Sharing • How can knowledge be managed and disseminated between AI systems and employees? • How can tacit knowledge be learned by AI systems?	**Coordination** • Will sequential, reciprocal, or pooled coordination be most effective for AI systems and employees? • How can relational coordination be developed?	**Socialization** • How can organizational factors influence adaptation to AI systems and collaborative robots? • How do anticipatory socialization factors change when AI and robotics are deeply integrated into a company culture?

What weights should be given to such systems as they gain increased control over various processes? How can one implement proper controls in a decision-making process when an AI system encounters an abnormality that requires human interaction? Future scholars should explore how managers manage the shrinking gap between AI and employee capabilities and how AI and employees proactively and jointly alter strategic decision-making.

Organizational cognition is another crucial research domain in the current context. It is now widely accepted that organizations *do learn* (Huber, 1991; March, 1991). However, adoption and subsequent integration of AI in organizations may mean deep and disruptive changes in their learning architectures. While many companies are already using big data inputs obtained from platforms such as social media, the integration of AI systems such as ANNs and deep learning models may imply fundamental shifts in the way organizations learn and absorb new knowledge. Newer AI technologies will compel companies to shift from the focused learning mindset (where learning occurs at specific stages of the value chain or in a particular task domain) to more complex and transformative learning (in which learning would occur across the value chain and may include partner organizations). The positive spillover effect of such learning will be jointly shared by the network/cluster organizations (Mudambi, Mudambi, Mukherjee, & Scalera, 2017). We foresee the emergence of a new organizational learning architecture (involving big data, data sharing, and cloud technology) driven by technologies such as deep learning and generative adversarial networks. Thus, it will be fruitful for future scholars to investigate how explorative and exploitative learning occurs with AI. How does the adoption and integration of sophisticated AI systems impact the learning architecture of organizations? For example, how do organization-level absorptive capacities need to change to ensure that such adoptions of sophisticated systems do not have debilitating effects on the organization-level learning processes?

This leads us to the importance of exploring the dynamics of AI and micro-foundations of knowledge management processes in the organizations. Ultimately, individuals and their actions are the building blocks of organization-level competitive advantage (Nuruzzaman, Gaur, & Sambharya, 2019), and the significance and viability of AI as a value-creating strategic device should depend on how knowledge is acquired, shared, assimilated, and reinforced between AI systems and individual employees. Thus, it will be worthwhile to examine how knowledge is acquired, shared, and utilized between AI and employees.

Next, relevant to relational research, we foresee an important set of questions related to AI as a team member and/or colleague. Team structure could be inherently changed as employees work side-by-side with AI machines. This is already occurring in some companies that utilize collaborative robotics. For example, in an automotive company in the Midwest, an AI robot is used to move several thousands of pounds of steel. The employee that previously held that job is now a partner with the robot such that if the AI system detects a defect in the product, the employee would be signaled to come inspect it. At times, it is just a piece of dust that causes the product to be wiped down before moving successfully through the production line. Without this collaboration, the AI robot may mistakenly label a product as defective, which could waste materials and increase cost for the company. Thus, the relational coordination mechanisms that could exist between man and machine should be explored.

In addition, as discussed in our typology of AI integration, there are a number of ways in which AI and employees may cooperate. The quadrants discussed in our model differ in the extent to which humans are involved in inputting data for AI systems, processing information, or interpreting output. Future research should examine how Input-Process-Output models (Ilgen, Hollenbeck, Johnson, & Jundt, 2005) of teams change when integrating AI systems. Relatedly, studies in the future should explicitly identify the type of collaboration needed based on our AI integration model and then determine how to adjust the socialization process accordingly. Moreover, relational issues such as team identity, team size, team trust, and team dynamics are significant considerations as changes to such elements occur in the workplace. Some perspectives suggest that AI-based systems can be “considered a member of the team” (Parry et al., 2016) and thus the adoption and integration of these technologies require an “informed, prudent, and realist approach” from organizational scholars and practitioners (von Krogh, 2018, p. 408). Frick (2015) succinctly emphasizes this point, stating that “as these machines evolve from tools to teammates, one thing is clear: Accepting them will be more than a matter of simply adopting new technology” (p. 146). For instance, as relational capabilities are more difficult to imitate by rivals, exploring how trust is developed and maintained in such hybrid teams in virtual contexts (Makarius & Larson, 2017), or what coordination capabilities (Mukherjee, Lahiri, Mukherjee, & Billing, 2012) are most appropriate in these situations, may help researchers decipher important sources of competitive advantage for AI adopting companies. Thus, the issues of trust, self-categorization, and identity are very pertinent in this regard and should be further explored.

Organizational structural issues will be influenced by AI systems in a variety of areas that have not yet been examined. Consider the new set of skills and capabilities needed for managers, employees, and AI to work together. A change in skills will usher in the necessity to redesign jobs and create new ones entirely. For example, an interview with an AI expert revealed that he expected to be a task creator changing the nature of human roles such as creating a specialist job to analyze potential cybersecurity threats detected by an AI system. New roles require training, especially a shift in predictive managerial tasks (hiring decisions, promotions, etc.) towards the ability to make decisions and understand the relationship between actions and outcomes (Agrawal, Gans, & Goldfarb, 2017). This will be important during the adaptation phase of the socialization process.

Questions remain regarding the creation of entirely new business units built to handle scouting, experimenting, supporting, and training AI tools in the organization (Di Fiore, Schneider & Farri, 2018). For instance, welcoming AI as an actual teammate has long-reaching effects on organizational design. Historically, tools such as enterprise resource planning (ERP) software are seen as "organization centered systems" (Kling et al., 1998), as they require human operators to bear the brunt of significantly altering their normal course of action. In contrast, "human centered systems" place the needs of human operators above all else, influencing design and deployment decisions to ensure limited disruption of current employee job structure (Kling et al., 1998). This could have major implications for organization-level variables such as turnover, organizational commitment and career satisfaction, as well as consumer-level variables such as loyalty and repurchase intention. AI-powered systems may give rise to a new category of hybrid form that focuses on the interaction between human and AI for efficient operations. This nexus of human-AI activity within the organization has already given rise to "AI centers of excellence" that serve as the hub for AI interactions (Davenport & Dasgupta, 2019). Thus, the fundamental issues related to structure and functioning in organizations in relation to AI systems remain underexplored. Future research can explore these issues to examine the "AI Readiness" of adopting organizations.

6. Discussion and conclusion

AI is set to fundamentally transform the future of work. We are currently witnessing a critical shift in the usage of AI systems during the ongoing COVID-19 pandemic crisis, a time that has, in many cases, required companies to increase AI-employee integration to continue safe and effective operations. For instance, in the tourism industry, the usage of Robots for reception and concierge services and AI-enabled chatbots for standard customer communication and questions, has substantially increased (Sigala, 2020), allowing greater safety for employees who can then focus on more complex interactions with customers. AI can be used to support essential jobs, such as upgraded ventilators that nurses and doctors can operate remotely. Robots in grocery stores perform cleaning tasks so that employees can focus on stocking shelves and ensuring that customers have the products they need in a time of crisis (Howard & Borenstein, 2020). The COVID-19 pandemic highlights the need for further AI-employee integration to enhance safety and obtain organizationally and socially valued outcomes worldwide.

Our analysis makes two distinct contributions to extant research. First, our proposed typology using the AI novelty and scope dimensions points toward different types of AI systems and AI-employee relationships that can be leveraged in studying the evolving complexity and resulting integration of AI and employee roles in the workplace. This is particularly important because although AI is increasingly being adopted in organizations, managers and employees have negative perceptions related to job substitution, training, and uncertainty (Frey & Osborne, 2017), lack understanding of why and how the AI should be used (Raisch & Krakowski, 2020), and have issues in trusting AI systems (Gunning, 2017). A better understanding of, and integration with, AI will help employees overcome some of these negative perceptions and opportunities that could result if a company focuses on building sociotechnical capital.

Our work also takes initial steps to develop a novel socialization framework that can be used by researchers and managers alike in studying how to successfully integrate AI into organizations. Effective socialization and integration of AI will allow organizations to rise with the machines rather than against them. Based on the socialization literature, our model advances a process that articulates how best to assuage the employee concerns associated with AI systems and gradually adopt, adapt, and assimilate them for complete transformation leading to organizationally valued outcomes. Moreover, we identify boundary conditions related to people and situations that mitigate or enhance the likelihood of AI-employee integration success. As the boundaries between human employees and AI continue to blur in the modern world, it may be time to redefine traditional work designs and processes to better guide future workers' experiences.

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